Modelling Black Market for Dollars in Sudan: Volatility Analysis

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Abstracts
To capture volatility dynamic in the black market for foreign exchange in Sudan, in this paper we allowed a quadratic response of volatility to good and bad news. Results of asymmetric conditional volatility of the black market rate indicate bad news have more significant impact on volatility of the black market rate than the impact of good news. Evidence of volatility persistence shows the black market price exhibit short memory behavior, implying price changes reflect most recent information. Analysis of impulse response effects show the market is unaffected by shocks in global fundamental factors. A policy implication of these results is that the pricing mechanism in the black market may not reflect a competitive pricing system. As a result, official exchange rate emulation of the black market rate, may lead to distortion of resource allocation in the economy.
Keywords: Black market, volatility, GARCH, Sudan.

Introduction

The increasing interest in studying black markets for foreign exchange in developing countries over the past few years is possibly due to the increasing size of these markets despite, successive attempts by some governments in the past decade to reduce the impact of black markets on official reserves. It has become apparent to many economists in recent years that a sound foreign exchange policy should consider the link between the black market for foreign exchange and the rest of the economy.

To contain the rising black market rate premium (ratio of the black market rate to official rate) and restore official reserve loss (due to rising premium) authorities in some countries have resorted instead to more restrictive foreign exchange policies in the official market by restricting import in the official market and in some cases by adopting periodic devaluations in an attempt to anchor the black market rate.

The link between black markets for foreign exchange and the rest of the economy depends on the size and the structure of the black markets, which differ from one country to another. In some countries the black market for foreign exchange has a large number of dealers. In these markets the price of foreign exchange is determined according to supply and demand for foreign currencies. In other countries the black markets are dominated by a small number of dealers who set prices on a daily basis, using their knowledge of supply and demand. Understanding the structure of black markets requires investigating the sources of supply and demand for foreign currencies.

Onour (1996) has reported that the inflow of foreign currencies to black markets comes in general from six sources: smuggling of exports, under-invoicing of exports, over-invoicing of imports, foreign tourism, and the inflow of remittances of national workers abroad, as well as the illegal diversion of foreign currency from the official market to the black market when the premium is high. All of these sources are likely to be seen jointly in many countries, but there is always a dominant source at each time and in each country, depending on the economic policies and sources of foreign currency in that specific country.Under-invoicing of exports, for example, is believed to have been a major source of foreign currency supply to the black market in Argentina for the period 1977-85 (Agenor, 1992). Export smuggling represented a major source of foreign currency supply of the black markets in India, Pakistan, and Turkey in the early seventies (Gupta, 1984). Foreign tourism is considered as a major source of supply in Caribbean countries (Agenor, 1992). Workers' remittances have represented the key source in Egypt (Bruton, 1983), Morocco, Bangladesh, and Sudan (Onour, 1996).

The demand for foreign currencies in the black markets mainly stems from three activities:legal and illegal imports, portfolio diversification and capital flight, and residents travel abroad. The portfolio motive is believed to be strong in high inflation economies, where real interest rates are very low, and where considerable uncertainty over economic policies prevails. In these situations foreign currency holdings represent a safeguard against domestic cuurncy depreciation. Portfolio diversification through the black market may also take place as a result of restrictions on private capital outflows through the official market.

In this paper we analyze volatility dynamics and structural change in the black market for dollars in Sudan during the period from January 2009 to May 2012.

The remaining part of the paper is structured as follows. Section two includes literiture review. In section three several preliminary statistics presented. Section four includes the methodology. Section five discusses estimation results. The final section concludes the study.

Literiture review

There are increasing evidences that volatility in asset markets in general is featured by fat-tailed distribution phenomena, Brooks and Persand (2003), Vilasus (2002), Hansen and Launda (2003), Bollerslev (1987). Studying volatility in asset markets in general can help controlling asset markets irregularities and detecting volatility boundaries (Bollerslev et al., 2003). The increasing sensitivity of major economic indicators in underdevolpoed economies to volatility in black market for foreign exchange highlights the importance of modeling distributional aspects of these markets.

Conditional volatility estimates using asymmetric leptukortic distributions is more robust for highly volatile series evidenced in a number of informal currency markets which have a higher degree of non-normality. The literature on black market for foreign exchange takes two approaches: the first approach adapt specification of determinants of black market rate premium. A partial list of articles in this tradition includes Dornbusch et al. (1983), Fishelson (1988), Culbertson (1989), Phylaktis (1992), and Shachmurove (1999). The second approach focuses on dynamic adjustment of the black market rate premium in search for stability conditions. A list of research in this direction includes Onour and Cameron (1997), Onour (2000), Edwards (1989), Kharas (1989), Lizondo (1989), Pinto (1989), Jadgeep and Vegh (1990).

Data analysis:

Data employed in this study includes daily data on Sudanese pound price per dollar in the black market for foreign exchange during the sample period from January 2009 to May 2012 . To accommodate the effect of structural change in dynamics of the black market for foreign exchange, the sample period divided into two sub-periods, the period before and after July 2011, which is the date when South Sudan seperated from the rest of the country, and loss of Sudan about 75 percent of oil revenue, resulting in foreign currency shortage in the official market for foreign exchange, and fast depreciation of the local currency price in terms of the dollar in the black market for foreign exchange.The sample period before July 2011 includes 700 observations, whereas the period after July 2011 includes 330 observations.

Summary statistics for each of the two periods presented in table (1).

Results in table (1) indicate unconditional volatility after July 2011 increased about ten times to its level before that period. The skewness and kurtosis coefficients reveal that the black market price exhibit peakness and fat tailedness relative to a normal distribution in both periods. The high values of kurtosis statistics indicate price distribution is characterized by high peakness (fat tailedness). The positive skewness results indicate a higher probability for currency price increase after July 2011. The Jarque-Bera (JB) test statistic provides evidence to reject the null-hypothesis of normality for the black market prices. The sample autocorrelation statistic indicated by Ljung-Box, Q (10) statistic, reject the null hypothesis of uncorrelated price for ten lags for both sample periods. The high values for $Q^2(10)$ test statistic suggest conditional homoskedasticity can be rejected in favor of serial interdependence of conditional volatility series. Augmented Dicky-Fuller (ADF) test for unit root reject the random walk hypothesis for both sample periods.

To test for strict white noise process that reflect sequence of independent and identically distributed (iid) random variables, Kocenda and Briatka (2005) test (known as (K2K)) employed to detect hidden non-linear dependence in the price series[1]. The result of K2K test, presented in table 2, confirm the significance of non-linear dependence in both series, implying rejection of the assumption of iid in the data.

Volatility modelling:

Asymmetry and fat-tailedness:

Although the simple GARCH specification is widely used in the empirical research of finance, there are substantial evidences that volatility of asset returns characterized by time varying asymmetry (Glosten, Jagannathan and Runkle (1993). As a result, to avoid misspecification of the conditional variance equation, a leverage term in the GARCH specification is included.

The GARCH-type specification introduced by Glosten, et al, (1993) allows a quadratic response of volatility to news with different coefficients for good and bad news, but maintains the assertion that the minimum volatility will result when there is no news[2]. Given that asset returns defined as:

[1] K2K test is more general form of BDS test used for non-linear dependence. Briatka, L. developed computer program for calculating K2K statistic (epsilon value) ranging between $(0.6\sigma, 1.9\sigma)$ with dimension 2 to 8.

[2] An appropriate specification of ARCH model requires knowledge of empirical regularities the model should capture. Among well documented regularities in the literature are thick tails that characterize asset returns, and volatility clustering, which refers to the phenomena that large changes in volatility tend to be followed by large changes of either sign, and small changes to be followed by small changes. Also another phenomena capured by ARCH specifications is the so-called leverage effect, which refers to the tendency for asset returns to be negatively correlated with changes in asset volatility.

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \mu + \varepsilon_t \qquad (1)$$

where

$$\varepsilon_t \mid \Psi_{t-1} = \sigma_t z_t$$

For p=q=1, GJR-GARCH model specify volatility as:

$$\sigma_t^{\,2} = w + (\alpha + \delta\, I_{t-1})\varepsilon^2{}_{t-1} + \beta\, \sigma^2{}_{t-1} \qquad (2)$$

where I_t indicator function equal to 1 when $\varepsilon_{t-1} < 0$, and zero otherwise. In this model good news (or positive shocks, $\varepsilon_{t-1} > 0$) have an impact of $\alpha\varepsilon^2{}_{t-1} \geq 0$ on volatility, while bad news or negative shocks, $\varepsilon_{t-1} < 0$) have an impact of $(\alpha + \delta\,)\varepsilon^2{}_{t-1} \geq 0$. Therefore if $\delta \neq 0$, we can say that there exist asymmetric effects on conditional volatility.

In the coming sections we estimate conditional volatility of change in black market rate based on the specifications in equation (1) and assuming the distribution of the standardized error term, z_t , is Student t-distribution (GJR-t), that is fat-tailed. It is important to notice that volatility specification in equation (2) takes into account leptokurtosis of asset price change that characterizes high frequency time series data. To capture leptokurtosis present in high frequency speculative price data, Bollerslev et al. (2003), suggest use of student t-distribution with degrees of freedom greater than two.

When the residual errors in (1) distributed Student t-distribution the density function in equation (1) can be specified as:

$$f(\varepsilon \setminus \eta) = \frac{\Gamma(\eta+1)/2}{\sqrt{\eta\pi}\,\Gamma(\eta/2)}\left(\frac{\eta}{\eta+\varepsilon^2}\right)^{(\eta+1)/2} \qquad for -\infty < \varepsilon < \infty \qquad (3)$$

where $\Gamma(.)$, denotes gamma function, and η is the degrees of freedom.

Table (1): descriptive Statistics

	Before7/2011	After7/2011
mean	2.36	2.14
St.deviation Max Min	0.14 2.81 2.22	1.34 4.09 -0.02
Skewness	-0.68	0.20
Ex.Kurtosis	12.32	-0.89
JB test (p-value)	4416* (0.00)	13.35* (0.00)

Q(10) (p-value) $Q^2(10)$ (p-value)	6505* (0.00) 6755* (0.00)	3013* (0.00) 2964* (0.00)
ADF unit root (critical value)	3.17 (6.25)	5.14 (6.25)

*Reject the null-hypothesis at 1% sig.level.

Table (2):Nonlinear dependence test (K2K)

Dimension	**Before 7/2011**	**After 7/2011**
2	0.568*	0.872*
3	0.584*	0.911*
4	0.598*	0.944*
5	0.61*	0.972*
6	0.62*	0.997*
7	0.628*	1.02*
8	0.637*	1.04*
9	0.644*	1.065*
10	0.651*	1.087*

Values in entries are K2K statistics. Critical values included in K2K computer program.
*All values of K2K reject the null-hypothesis of iid, at 1% significance level.

4.2 – Volatility persistence

4.2.1 – The ARFIMA (p,d,q) process

The ARFIMA(p,d,q) model can be stated as:

$$\phi(L)(1-L)^d(y_t-\mu)=\theta(L)\varepsilon_t \qquad (4)$$

where

$$\phi(L)=\sum_{j=1}^{p}\phi_j L^j\ ,\quad \theta(L)=\sum_{j=1}^{q}\theta_j L^j\ ,$$

$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(k+1)\Gamma(-d)}$$

and L is lag operator, d is fractional differencing parameter, all roots of $\phi(L)$ and $\theta(L)$ assumed to lie out side the unit circle, and ε_t is white noise.

GARCH(p,q) models attempt to account for volatility persistence, but with the feature that persistence decays relatively fast. However, in some cases volatility shows very long temporal dependence, i.e., the autocorrelation function decays very slowly.

This motivates consideration of Fractionally Integrated Generalized Autoregressive Conditional Hetroskedasticity (FIGARCH) process (Baillie et al, 1996) defined as:

$$\varphi(L)(1-L)^{d}\varepsilon_t^{\ 2} = w + \{1-\beta(L)\}v_t \qquad (5)$$

where $\varphi(L)$ *and* $\beta(L)$ are respectively the AR(p) and MA(q) vector coefficients and $v_t = \varepsilon_t^{\ 2} - \sigma_t^{\ 2}$,

Following Baillie et al (1996), Bollerslev and Mikkelsen (1996), Granger and Ding (1996), the parameters in the ARFIMA(p,d,q) and FIGARCH(p,d,q) models in (4) and (5) estimated using quasi-maximum likelihood (QMLE) method. In the ARFIMA models, the short-run behavior of the data series is represented by the conventional ARMA parameters, while the long-run dependence can be captured by the fractional differencing parameter, d. A similar result also applies when modeling conditional variance, as in equation (5). While for the covariance stationary GARCH(p,q) model a shock to future conditional variance dies out at an exponential rate, for the FIGARCH(p,d,q) model the effect of a shock to the future conditional variance decay at low hyperbolic rate. As a result, the fractional differencing parameter, d, in equation (5) can be regarded the decay rate of a shock to the conditional variance (Bollerslev, 1996).

In general, allowing for values of d in the range between zero and unity (or, 0<d<1) add a flexibility that play an important role in modeling long-run dependence in time series[3].

Bollerslev (1996) indicates that if d=0, the series is covariance stationary and possess short memory process, whereas in the case of d=1 the series is non-stationary. However, in the case of 0<d<0.5, the series even though covariance stationary, its auto-covariance decays much more slowly than ARMA process.

If d is 0.5<d<1 the series is no longer covariance stationary, but still mean reverting with the effect of a shock persist for a long period of time, and in that case the process is said to have a long memory. Given a discrete time series, y_t, with autocorrelation function, ρ_j, at lag j, Mcleod and Hipel (1978) define long memory as a process:

$$\sum_{j=-n}^{n}\left|\rho_j\right| \qquad as \quad n \to \infty \qquad (6)$$

[3] See Diebold and Rudebuch (1989), Cunado et al. (2005), and Granger and Ding (1996) for a detailed discussion about the importance of allowing for non-integer values of integration when modeling long-run dependence in the conditional mean of time series data.

characterized as nonfinite. In the non-stationary and in the long memory process a shock at time t, continues to influence future y_{t+k} for a longer horizon, k, than would be the case for the standard stationary ARMA process. While there are varieties of ways to estimate the parameters of equation (5), we employed in this paper the maximum likelihood estimator.

The role of fundamentals:

To assess the transmission effect of global shocks on the black market we employed imulse response analysis using international gold price, crude oil price, global food price, and international dollar price in terms of Euro currency as global fundamental factors.The international gold price is taken as a proxy variable to change in the central bank reserve ratio, as well as an alternative investment choice. Crude oil price shock reflect the government limited choice in financing government imports which is influenced by shocks on international crude oil markets. Global food price reflect the international inflation rate

The international dollar price shock reflect the impact of global currency markets on black market for dollar in Sudan. The relationship between shocks on these variables and the black market can be set as follows:

$$\Delta B_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i \, e_{i,t}^2$$

Where B is the black market price, and e_i^2 is a shock corresponding to each of the five variables, derived from AR(1) process:

$$R_t = \beta_0 + \beta R_{t-1} + e_t$$

Where R_t is change in explanatory variable.

Estimation results

To estimate parameters in equations (1) - (4), maximum likelihood estimation employed. Table (3) presents estimation results of asymmetric conditional volatility (GJR–t distribution). The significance of the negative news coefficient (δ) for both periods reveal bad news have more significant impact on volatility than good news (α). However, the impact of good news have substantially changed from 2% before July 2011 to about 4% after this period, indicating that the market is becoming slightly more sensitive to good news. The significance of the (β) coefficient in the second period reveal volatility interdependence. The log-likelihood function and the information criteria (AIC) strongly suggest that GJR-t model is an appropriate specification for conditional volatility modelling in the two periods. GJR-t specification of conditional volatility is not only have high values of LLF but also have smaller values of AIC in the two periods.

Since d is 0<d<0.5 , in the ARFIMA(1,d,0) results (table (4)), then change in black market prices exhibit short memory behavior, indicating the relevance of current and most recent information in influencing price changes. Table (5) present results of volatility persistence of FIGARCH model. The sign and size of the $\hat{d}$ parameter support the evidence that shocks on black market are not likely to persist for long period, implying the speed at which adjustment process takes place when the market hit by a shock. This result is an indication of the market imperfection because as the market is controlled by fewer traders the transmission of information among market participants takes shorter time. Table (6) show weak link of black market price with shocks in international gold price, crude oil price, and international food price index.

Table 3 – GJR t-dist parameters

	Before7/2011	**After7/2011**
w **(p-value)**	-0.00* (0.00)	-0.00* (0.00)
α **(p-value)**	0.02* (0.00)	0.041* (0.00)
δ **(p-value)**	1.00* (0.00)	1.01* (0.00)
β **(p-value)**	0.00 (0.97)	0.02* (0.01)
LLF	5739	2370
AIC	0.42E-8	0.34E-7

Notes: Estimation values rounded into two decimals.
*significant at 5% significance level.

Table (4): ARFIMA (1,d,0)

parameters	Before 7/2011	After 7/2011
μ t-stat	0.007* (21.6)	0.001 (1.47)
ϕ t-stat	0.066* (2.42)	0.513* (23.7)
θ t-stat	-0.001 (-0.04)	-0.71* (-31.61)
d t-stat	0.98* (1883)	0.99* (416)
Log-likelihood	4145	1569

*significant at 5% significance level.
Estimation of ARFIMA(1,d,1) also yield similar results.
Estimation of parameters carried out using MLE method and DFP nonlinear algorithm.

Table (5): FIGARCH(1,d,0)

parameters	Before 7/2011	After 7/2011
ω (t-stat)	126.7 (0.71)	45 (1.87)
ϕ (t-stat)	-0.14* (-2.14)	-0.14 (-1.87)
d (t-stat)	0.18* (3.07)	0.39* (4.12)
Log-likelihood	4287	1018

Estimation of parameters carried out using DFP nonlinear algorithm.
*significant at 1 per cent level.

Table 6:The role of fundamentals

variable	GLS	OLS
α_1 (p-value)	0.33 (0.40)	0.32 (0.44)
α_2 (p-value)	0.32* (0.09)	0.31* (0.10)
$\alpha 3$ (p-value)	-0.069 (0.86)	-0.08 (0.83)
$\alpha 4$ (p-value)	0.069 (0.86)	0.042 (0.91)
Constant (p-value)	0.005 (0.62)	0.005 (0.60)
LLF	43.8	43.4
R^2	0.21	0.20
AIC	0.06	0.003

α_1 = the impact of international gold price shock.
α_2 = the impact of oil price shock.
α_3 = the impact of global food price shock.
α_4 = the impact of international dollar price shock (Euro per US dollar)
*significant at 10% significance level.

Concluding Remarks:

To capture dynamics of black market for foreign exchange in Sudan, we allowed in this paper a quadratic response of volatility to good and bad news during two sub-periods, before and after July 2011, the date when South Sudan seperated from the rest of the country. The log-likelihood function and the information criteria (AIC) strongly suggest that the asymmetric conditional volatility with fat-tailed distribution (GJR-t model) is appropriate specification of modelling conditional volatility in the black market for foreign exchange. Results of asymmetric conditional volatility in the black market price indicate bad news have more significant impact on volatility of the black market price than the impact of good news during the two periods. This reveals pessimistic views held by currency traders about the performance of the economy before and after the country split. However, the impact of good news have slightly changed from 2 percent before the period July 2011 to about 4 percent after this period, indicating foreign currency shortage after July 2011 made the black market rate slightly more responsive to good news. In general there is no significant structural change in the behavior of the black market volatility in the two periods, implying weak response of the black market to change in fundamentals. The ARFIMA(1,d,0) results support the evidence that change in black market prices exhibit short memory behavior, indicating price changes reveal only most recent information during each of the two sub-sample periods. Results of volatility persistance (FIGARCH model) also support evidence that the impact of shocks on the black market is likely to persist for short period.

Our findings also reveal insignificant role for global fundamental factors, such as international gold price, the US dollar price in international currency markets, and international food price index, on black market price changes. However, shocks in global crude oil prices exhibit marginal significance effect on the black market rate.

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